PROTECTING WIKIPEDIA FROM DISINFORMATION: DETECTING MALICIOUS EDITORS AND PAGES TO PROTECT

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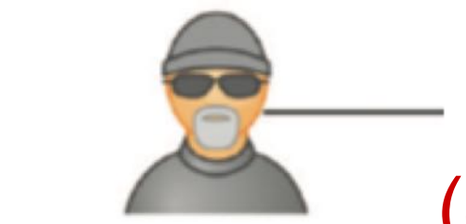
DISINFORMATION IN WIKIPEDIA

- Freely accessible
- Large reach
- Major source of information for many



Malicious Editor

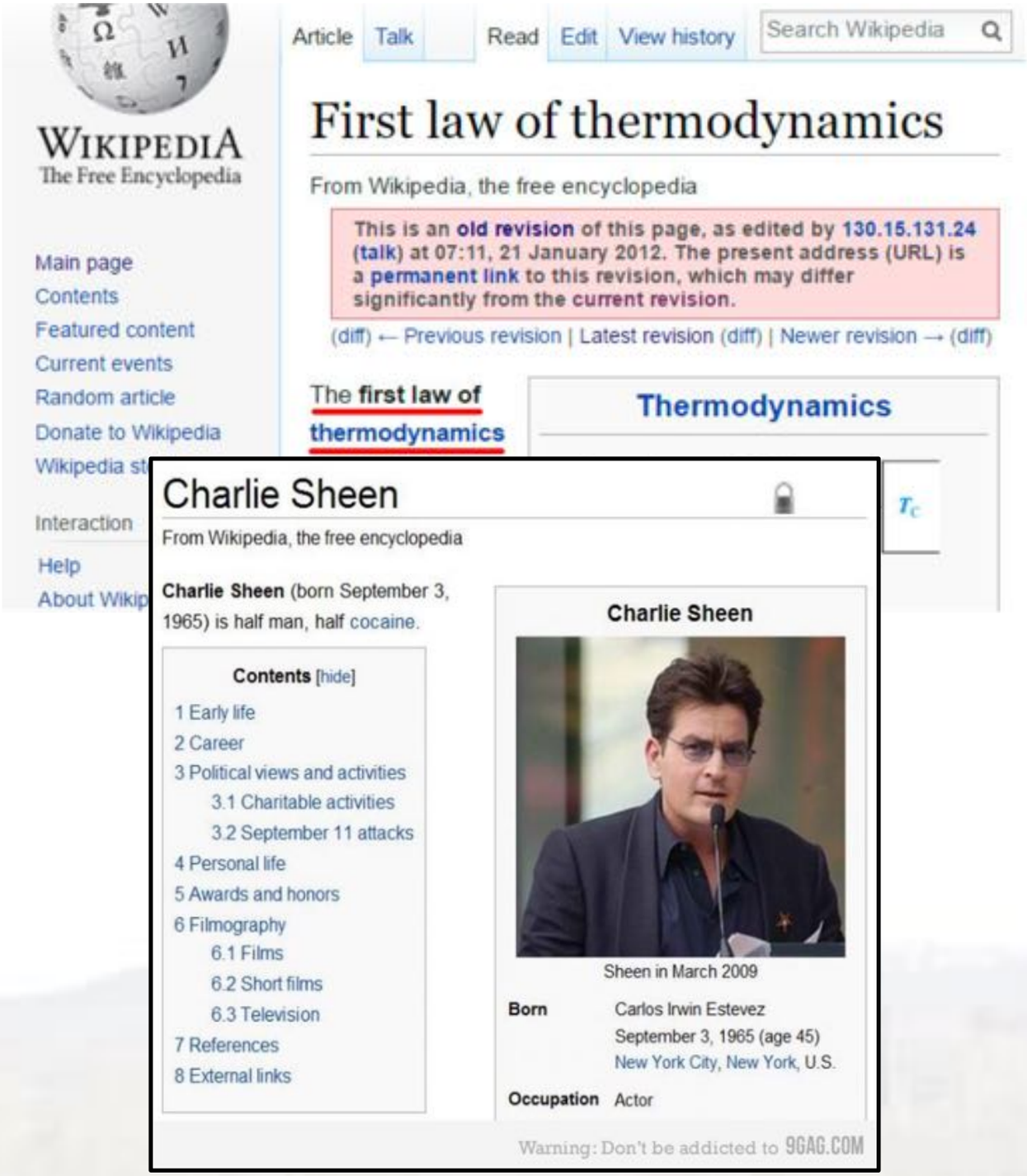
Vandals
Spammers
(Sockpuppets)

Easy to compromise article quality

WIKIPEDIA

The free encyclopedia that anyone can edit

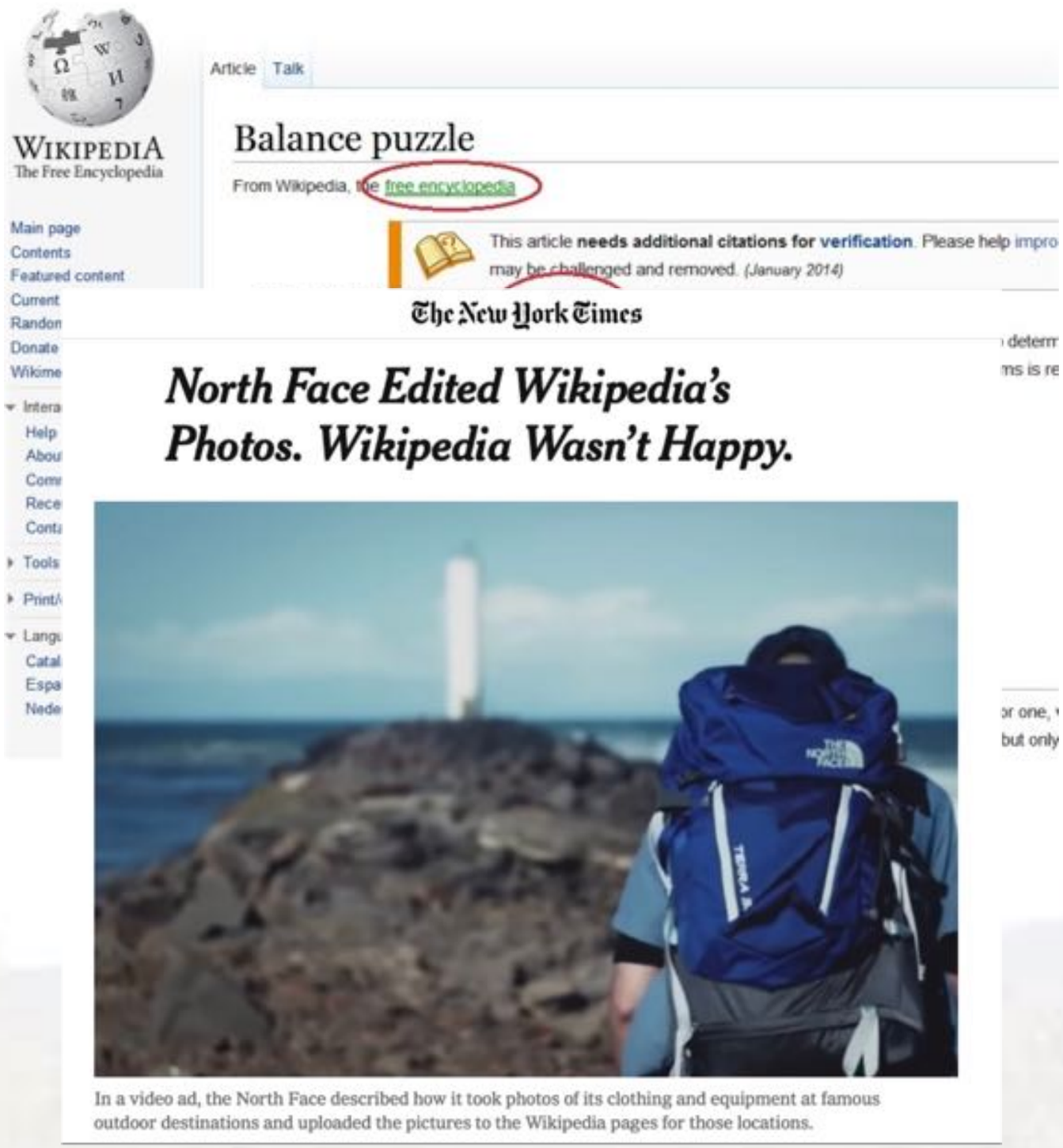
DISINFORMATION IN WIKIPEDIA



Vandalism

"the act of editing the project in a malicious manner that is intentionally disruptive. Vandalism includes the addition, removal, or modification of the text or other material that is either humorous, nonsensical, a hoax, or that is an offensive, humiliating, or otherwise degrading nature."

DISINFORMATION IN WIKIPEDIA



Spam

Unsolicited promotion of some entity

"There are three main types of spam on Wikipedia. These are:

- *advertisements masquerading as articles and contributions to articles;*
- *external link spamming; and*
- *adding references with the aim of promoting the author or the work being referenced."*

DISINFORMATION IN WIKIPEDIA

Olimar The Wondercat

From Wikipedia, the free encyclopedia

1 Episodes: series 1
2 Episodes: series 2
3 Foreign language versio
4 References

Episodes: series

1. Meet Olimar
2. Bye mum!
3. A long train journey
4. Olimar goes to Lon

Wikipedia:List of hoaxes on Wikipedia

From Wikipedia, the free encyclopedia

Contents [hide]

Hoaxes

Articles that deceptively present false information as a fact.

PROTECTING WIKIPEDIA

Good Editors/Users

- Rollbackers
- Patrollers
- Watchlisters
- Readers

Bots/Tools/Blacklists

- Cluebot NG
- Stiki
- ORES
- Link-spam blacklist

Page Protection

Account blocking

PROTECTING WIKIPEDIA:
RESEARCH EFFORTS

Detecting Disinformation

- Vandalism [Adler et al., CICLing 2011] (survey)
- Link-spamming [West et al., OpenSym'11], [West et al., CEAS'11]
- Hoaxes [Kumar,West,Leskovec, WWW'16]

Detecting Deceivers

- **Vandals**: *users who make incoherent and destructive edits* [Kumar,**Spezzano**,Subrahmanian, KDD'15]
- **Spammers**: *users who unsolicitedly promote of some entity* [Green & **Spezzano**, ICWSM'17]
- **Sockpuppets**: *multiple accounts operated by the same user. They are often used to deceive, e.g. to harass other users or to circumvent a block or ban.* [Solorio,Hasan,Mizan, LASM'13], [Yamak et al., WWW'16 Comp.]

Detecting Pages to Protect

- **Page protection**: *placing restrictions on the type of users that can edit a page* [Suyehira & **Spezzano**, CIKM'16], [Suyehira,**Spezzano**,Gundala, SNAM'19]

DETECTING MALICIOUS EDITORS: VANDALS AND SPAMMERS

DETECTING MALICIOUS EDITORS: VANDALS AND SPAMMERS

S. Kumar, **F. Spezzano**, and V. Subrahmanian
VEWS: A Wikipedia Vandal Early Warning System
SIGKDD, 2015

HOW DO VANDALS BEHAVE?

Dataset

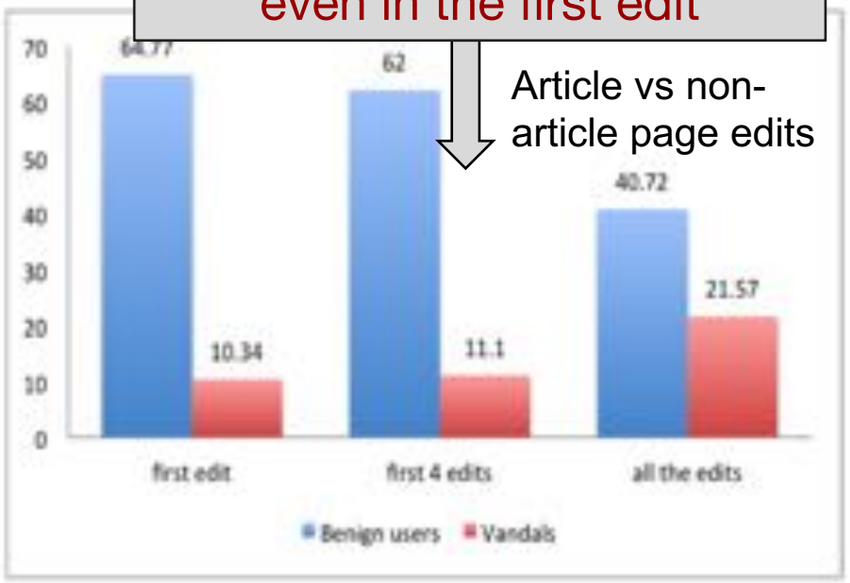
34,000 Editors *Half are vandals*

770,000 Edits *160,000 edits by vandals*

Jan 2013 - July 2014 new users

Benign users edit more non-article pages than vandals, even in the first edit

Article vs non-article page edits



Vandals spend less time in editing a new page

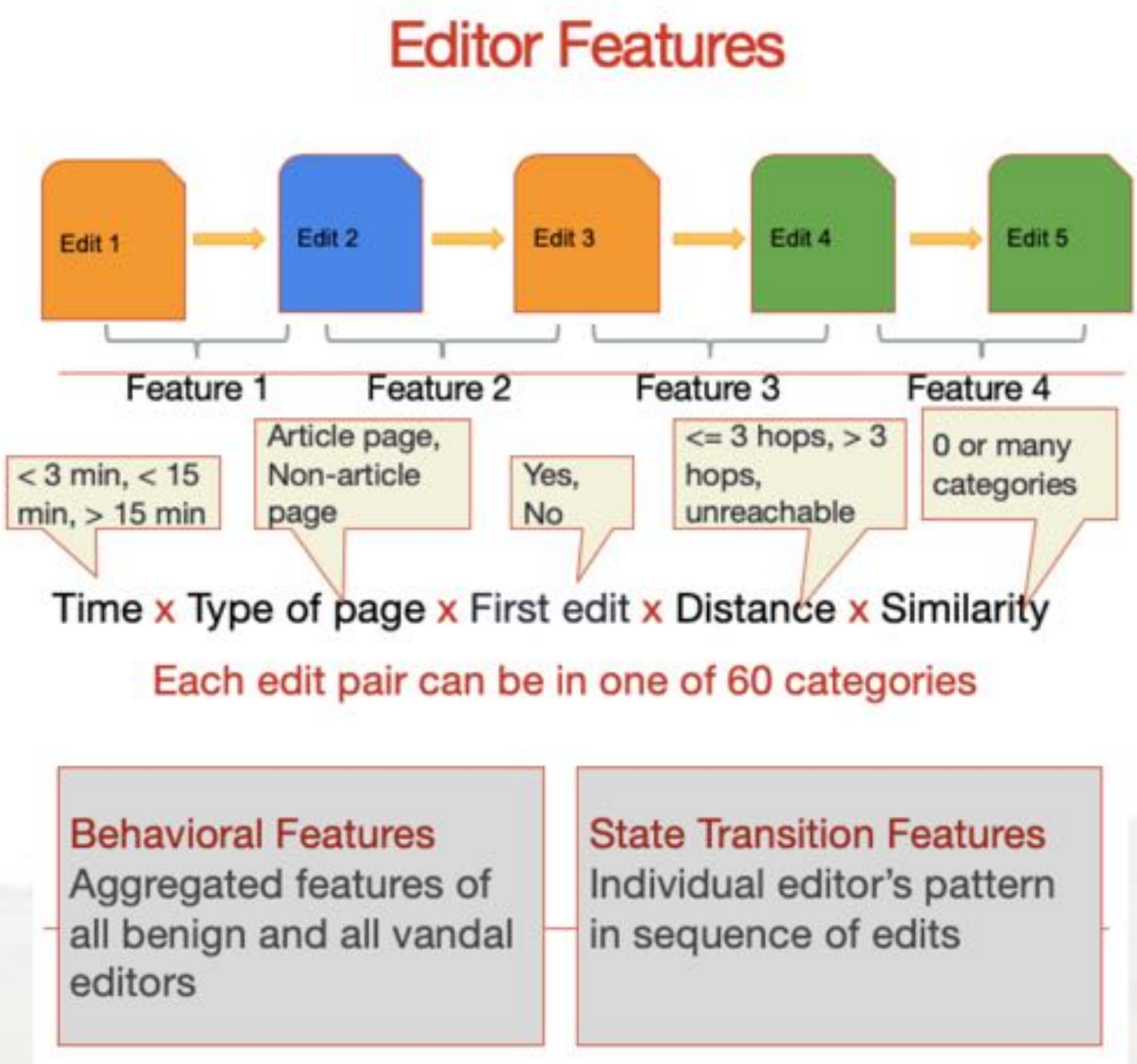
All edits

Edit of a new page

*All results are statistically different with p-values < 0.01

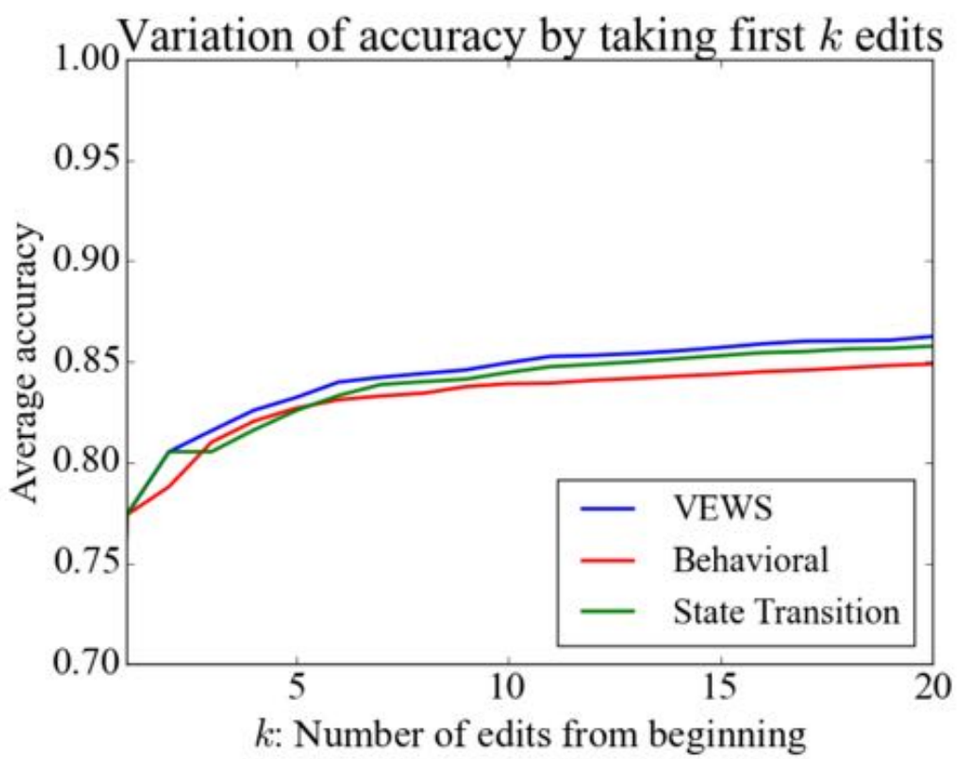
Vandals make faster edits than benign users

VEWS: VANDALS EARLY WARNING SYSTEM



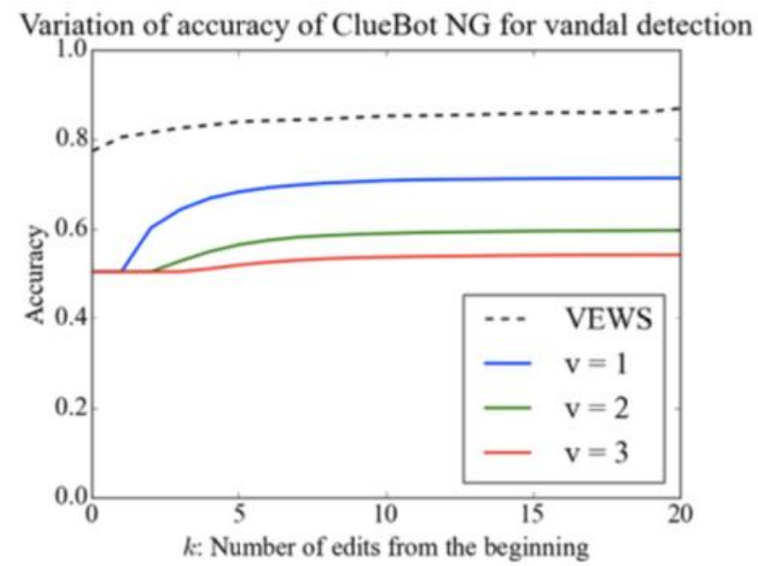
DETECTING VANDALS WITH VEWS

Accuracy of VEWS

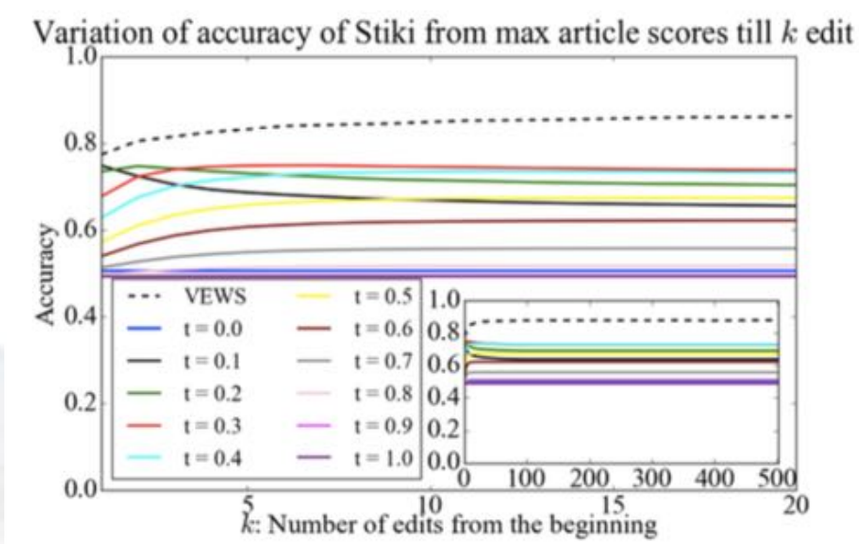


78% accuracy with first edit only.
44% cases vandal identified before first reversion.
VEWS detects vandals 2.39 edits before ClueBot NG, on avg.
With all edits, VEWS = 88% accuracy

VEWS vs. ClueBot NG



VEWS vs. STiki



DETECTING MALICIOUS EDITORS: VANDALS AND SPAMMERS

T. Green and **F. Spezzano**
Spam Users Identification in Wikipedia via Editing Behavior
ICWSM, 2017

DETECTING WIKIPEDIA SPAMMERS

Spam Dataset

*Our Spam dataset consists of **4.2K** (half spam and half benign) users and **75.6K** edits.*

- *All Wikipedia users (up to Nov. 17, 2016) who were blocked for spamming (**2,087 spammers**): "Wikipedians who are indefinitely blocked for spamming" (till Mar 12, 2009); "Wikipedians who are indefinitely blocked for link spamming" (after Mar 12, 2009)*
- *An almost equal number of randomly selected benign users (**2,119 benign users**).*
- *Up to the last 500 most recent edits for each user.*

Editor Features

Edit size based features

- *Average size of edits*
- *Standard deviation of edit sizes*
- *Variance Significance*: stdDev/avgSize

Editing time behavior based features

- *Average time between edits*
- *Standard deviation of time between edits*

Links in edit based features

- *Unique link ratio (only link domain)*
- *Link ratio in edits*

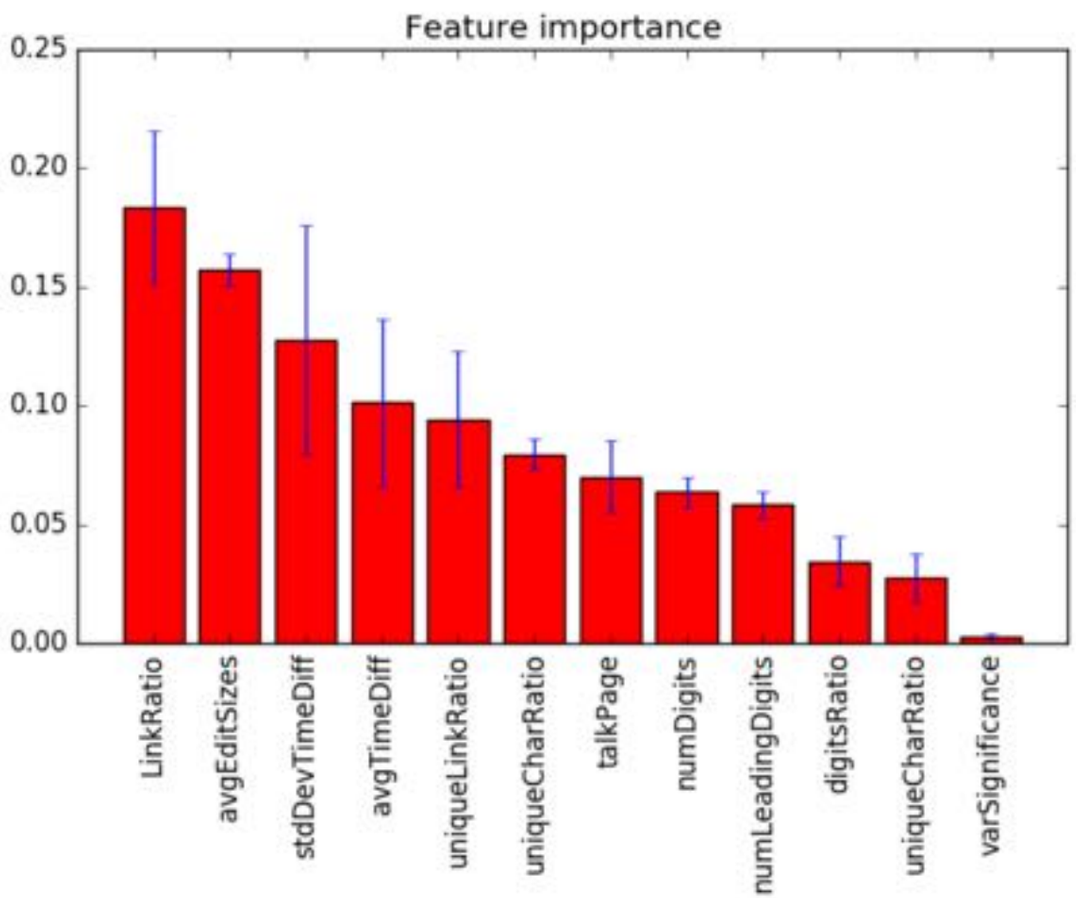
Talk page edit ratio

Ratio of talk pages correspondent to edited pages

Username based features

- *Number of digits in a username*
- *Ratio of digits in a username*
- *Number of leading digits in a username*
- *Unique character ratio in a username*

DETECTING WIKIPEDIA SPAMMERS:
FEATURE ANALYSIS



Top-3 Features

- Link Ratio
- Average size of edits
- Standard deviation of time between edits

Only 30.3% of the users edit talk pages. Among these, the **talk page edit ratio** is higher, on average, for spammers (0.2) than for benign users (0.081).

Username based features contribute to an increase in accuracy prediction by 2.9% (from 77.9% to 80.8%) and mean average precision by 0.019 (from 0.861 to 0.880).

DETECTING WIKIPEDIA SPAMMERS:
ACCURACY RESULTS

We can classify spammers from benign users with **80.8%** of **accuracy** and a **mean average precision** of **0.88** on 10-fold cross validation.

Our Features	Accuracy	MAP
SVM	67.0%	0.746
Logistic Regression	79.2%	0.838
K Nearest Neighbor	71.1%	0.733
Random Forest	80.5%	0.856
XGBoost	**80.8%**	**0.880**
	Accuracy	**MAP**
ORES	69.7%	0.695
ORES + Our Features	**82.1%**	**0.886**

Table: accuracy and MAP results and comparison with baselines. ORES and ORES + Our Features are computed with XGBoost.

ORES baseline: average and maximum ORES damaging score among all user's edits

Unbalanced Setting: 10% spammers and 90% benign users.

	AUROC
ORES	0.736
Our Features	0.842
ORES + Our Features	0.864

Table: Our features vs. ORES in the unbalanced setting. Everything is computed with XGBoost. The AUROC for the balanced setting is 0.891.

DETECTING PAGES TO PROTECT

K. Suyehira and **F. Spezzano**
DePP: A System for Detecting Pages to Protect in Wikipedia, CIKM, 2016.

F. Spezzano, K. Suyehira, and L. Gundala
Detecting Pages to Protect in Wikipedia across Multiple Languages
In Social Networks Analysis and Mining 9(1): 10:1-10:16, 2019.

WIKIPEDIA PAGE PROTECTION

When an article is heavily vandalized, or because of libel or edit-warring, administrators may protect the page by restricting its access to ”good” users

PROTECTING PAGES: POLICY

There are different levels of page protection:

Fully protected pages can be edited (or moved) only by administrators;
Semi-protected pages can be edited only by *autoconfirmed* users;
Move protection does not allow pages to be moved to a new title, except by an administrator.

Page protections can also be set for different amounts of time, including 24 or 36 hours, or indefinitely.

Currently, all the work is *manually* done by autoconfirmed editors and administrators.

DEPP: DETECTING PAGES TO PROTECT

DePP is the *first* system that is able to decide whether a page should be protected or not in Wikipedia.

Two novel sets of features based on:

1. **Page revision behavior** (features describing how users edit the page)
2. **Page categories** (proxy for page topic)

Advantages: **DePP** does not look at textual content, so it can work with all the different language versions of Wikipedia

DEPP: DETECTING PAGES TO PROTECT

- We build 4 datasets from different Wikipedia versions: English, German, French, Italian.

Dataset	Protected Pages	Non-protected Pages
English	6,799	6,824
German	1722	1706
French	524	512
Italian	171	168

- Each dataset consists of:
  - Half protected and half unprotected Wikipedia pages.
    - All edit protected articles up to Oct. 12, 2016.
    - An almost equal number of randomly selected unprotected pages.
  - Up to the last 500 most recent revisions for each selected page.

DEPP: DETECTING PAGES TO PROTECT

The **DePP** system achieves at least **0.93 accuracy** across multiple languages.

Accuracy

Dataset	B1	B2	B3	B1+B2+B3	DePP
English	0.56	0.67	0.73	0.80	**0.98**
German	0.50	-	0.50	0.50	**0.98**
French	0.50	0.77	0.50	0.77	**0.97**
Italian	0.50	-	0.50	0.50	**0.93**

Baselines:

[B1] Number of revisions tagged as "Possible libel or vandalism";

[B2] Number of revisions reverted as possible vandalism by any tool: Cluebot_NG or Stiki (English), *Salebot* (French), no tool available in German or Italian;

[B3] Number of edit wars between two users in the page: there was an explicit tag for German and Italian Wikipedia.

PAGES PROTECTION AND CONTROVERSIAL TOPICS

Protect from edit-wars → Controversial topics

Detecting controversial pages in Wikipedia by analyzing the page, the editing behavior, or neighborhoods

[Kittur et al., *CHI'07*], [Sepehri Rad and Barbosa, WikiSym'12], [Dori-Hacohen and Allan, *ECIR'15*]

Another Baseline: Can we detect pages to protect from their controversy level?

Dataset from [Dori-Hacohen and Allan, *ECIR'15*]:

2060 English Wikipedia pages annotated with their controversy level from 1 to 4 (193 are protected pages).

	AUROC	Avg. Precision
Controversy Level	0.53	0.12

PAGES PROTECTION PAGE POPULARITY

Is there any association between the popularity of a page and page protection?

We defined page popularity as number of page views.

Retrieved from the Wikipedia Clickstream dataset which contains monthly request logs of Wikipedia pages from other Wikipedia pages and any other Web page external to Wikipedia.

	Protected	Unprotected
More than 10 views	21.35%	11.6%
Avg. number of views	71.4K	1.1K

	AUROC	Avg. Precision
Controversy Level	0.53	0.12
Page Popularity	0.60	0.57

CONCLUSIONS

- People trust and read Wikipedia every day. Need to protect Wikipedia from disinformation:
  a) We presented DePP, an automatic tool to detect pages to protect in Wikipedia across multiple languages.
  b) We showed that behavior modeling can be very effective to detect malicious editors in Wikipedia (e.g., vandals and spammers).

Drawback of anti-vandal tools [Halfaker et al., 2013]

- Many newcomers face social barriers preventing them from the integration in the editor community, with the consequence of stop editing after a certain period of time.
- **Future work**: Improve our malicious editor detection tools by detecting these users as soon as possible and reduce false positives.

Thank you!

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